Int J Appl Earth Obs Geoinformation 67 (2018) 123–134

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Research paper

Simultaneous comparison and assessment of eight remotely sensed maps of Philippine forests

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ARTICLE INFO

Keywords:
ALOS
CCI
Forest
Global tree canopy
GLOBELAND30
Google Earth
LANDSAT
MODIS
NAMRIA
Philippines
Remote sensing

ABSTRACT

This article compares and assesses eight remotely sensed maps of Philippine forest cover in the year 2010. We examined eight Forest versus Non-Forest maps reclassified from eight land cover products: the Philippine Land Cover, the Climate Change Initiative (CCI) Land Cover, the Landsat Vegetation Continuous Fields (VCF), the MODIS VCF, the MODIS Land Cover Type product (MCD12Q1), the Global Tree Canopy Cover, the ALOS-PALSAR Forest/Non-Forest Map, and the GlobeLand30. The reference data consisted of 9852 randomly distributed sample points interpreted from Google Earth. We created methods to assess the maps and their combinations. Results show that the percentage of the Philippines covered by forest ranges among the maps from a low of 23% for the Philippine Land Cover to a high of 67% for GlobeLand30. Landsat VCF estimates 36% forest cover, which is closest to the 37% estimate based on the reference data. The eight maps plus the reference data agree unanimously on 30% of the sample points, of which 11% are attributable to forest and 19% to non-forest. The overall disagreement between the reference data and Philippine Land Cover is 21%, which is the least among the eight Forest versus Non-Forest maps. About half of the 9852 points have a nested structure such that the forest in a given dataset is a subset of the forest in the datasets that have more forest than the given dataset. The variation among the maps regarding forest quantity and allocation relates to the combined effects of the various definitions of forest and classification errors. Scientists and policy makers must consider these insights when producing future forest cover maps and when establishing benchmarks for forest cover monitoring.

1. Introduction

Forests supply ecosystem services that are essential for human survival. However, over half of the world's forests have been lost during the last 8000 years due primarily to human activities (Bryant et al., 1997; Shimada et al., 2014). Data from FAO's global forest resources assessment show that the world's forest cover continues to decline from 4.13 billion ha in 1990 to 4.06 billion ha in 2000, 4.03 billion ha in 2005, 4.02 billion ha in 2010, and 4.00 billion ha in 2015 (FAO, 2016). Thus, the monitoring of the world's remaining forest cover is a global priority.

The Philippines is among the world's 18 mega biodiversity countries due to its diverse habitats and high rates of endemism (PAWB, 2009; BMB, 2014). The Philippines maintains 5% of the world's flora and is ranked fifth globally in terms of the number of plant species (PAWB, 2009). However, the Philippines has become one of the world's hotspots where biodiversity is threatened due to exotic species, mining and land change, especially deforestation (Myers et al., 2000; PAWB, 2009; Lasco et al., 2013; BMB, 2014). The Philippines ranks fourth on the Conservation International's list of the world's most threatened forest hotspots (Conservation International, 2011).

The forest cover of the country has been changing rapidly, declining from 90% in 1521 when Spanish colonizers arrived to 70% in 1900 and then to 22% in 1998 (ESSC, 1999). Population increase, urban growth, agricultural expansion, and timber harvesting are among the most important drivers of deforestation in the country (Kummer, 1992; Liu

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https://doi.org/10.1016/j.jag.2017.10.008
Received 15 January 2017; Received in revised form 19 October 2017; Accepted 29 October 2017
Available online 02 February 2018
0303-2434/

et al., 1993; ESSC, 1999; Lasco et al., 2013). Consequently, the protection, conservation and improvement of the country's remaining forests have become major concerns to the national government and to other organizations.

Numerous reforestation projects and management policies in the Philippines have emerged during the last century (Harrison et al., 2004; Lasco et al., 2013). The most recent reforestation initiative of the Philippine government is the National Greening Program (NGP). NGP's main objective was to plant 1.5 billion trees on 1.5 million hectares from 2011 to 2016 (RP, 2011). Like previous reforestation projects, the challenge lies in monitoring NGP's impact, which requires accurate baseline information.

Remote sensing is an important source of information for forest cover monitoring across various spatial and temporal scales. The advances in remote sensing technology have enabled the production of various global forest and land cover products that can serve as benchmarks for monitoring future forest cover changes. Examples of these products include the GlobeLand30 (Chen et al., 2015), the Global Tree Canopy Cover (Hansen et al., 2013), the ALOS-PALSAR Forest/Non-Forest Map (Shimada et al., 2014), and the Landsat Vegetation Continuous Fields (Sexton et al., 2013).

However, various types of remotely sensed data and various forest classification procedures can produce various estimates of forest cover. For instance, according to the GlobeLand30 estimate, the Philippines had 19.8 million ha of forest cover in 2010 (Chen et al., 2015). In the same year, the ALOS-PALSAR Forest/Non-Forest Map (Shimada et al., 2014), the Global Tree Canopy Cover (Hansen et al., 2013) (forest > 50%) and the Landsat Vegetation Continuous Fields (Sexton et al., 2013) (forest > 50%) estimated 16.8, 16.8, and 10.6 million ha, respectively. Meanwhile, the Philippine Land Cover map of 2010 produced by the National Mapping and Resource Information Authority (NAMRIA) estimated 6.8 million ha (Manuel, 2014; DENR, 2015). This muddle of estimates causes confusion and can potentially affect forest cover monitoring and forest management planning. Thus, it is necessary to assess and compare these forest and land cover products simultaneously.

Many studies have compared and assessed various remote sensing-derived global forest and land cover products. Recent ones that are closely related to this study include Yang et al. (2017), Sexton et al. (2015) and Bai et al. (2014). Bai et al. (2014) compared and assessed five moderate-resolution global land cover products covering China, circa year 2000. Their comparison of the land cover products with reference data revealed disagreement that ranges from 48% to 67%. Bai et al. (2014) hypothesize that the disagreements could have been due to differences in the satellite sensors, time points, classification algorithms, or classification schemes.

Sexton et al. (2015) assessed the agreement of eight global land cover products for the class forest in or near the year 2000. Their study revealed that areas with high forest disagreement and uncertainty are in sparsely forested regions. They also argued that the observed disagreement is due to the many definitions of the term 'forest'. The authors write that due to "different geographic and cultural backgrounds, even expert human interpreters disagree on the identification of forests in situ or in satellite images" (p. 192).

Yang et al. (2017) compared and assessed eight medium-resolution forest cover maps in 2010 on the Loess Plateau, China. The authors used Google Earth images captured around 2010 and field photos taken during 2010–2013 to interpret visually 100 forest and 493 non-forest regions. Their forest omission error intensity ranged from 7% to 48% and their forest commission error intensity ranged from 6% to 28%. The potential reasons for the observed disagreements between the forest cover maps included variation in forest definitions, data sources, and algorithms (Yang et al., 2017).

Our study builds on these previous studies as we compare and assess eight remotely sensed maps of Philippine forest cover in the year 2010 by quantifying their agreements and disagreements. Our goal is to provide insights regarding the potential sources of disagreements among the maps and to discuss the implications of such disagreements for forest cover monitoring. Our manuscript makes a unique contribution to methodology in that we have created a technique to compare multiple maps simultaneously in terms of quantity and allocation of a category, which is forest in our case.

2. Methodology

2.1. Land cover data, reclassification, and reference data preparation

We compared and assessed eight maps of forest versus non-forest of the Philippines in 2010 derived from eight remotely sensed land cover products. One of these products is the Philippine Land Cover produced by NAMRIA (Manuel, 2014; DENR, 2015), which has national coverage. The other seven products have global coverage. They are the Climate Change Initiative (CCI) Land Cover (ESA, 2017), the Landsat Vegetation Continuous Fields (VCF) (Sexton et al., 2013), the MODIS VCF (DiMiceli et al., 2011), the MODIS Land Cover Type product (MCD12Q1) (Friedl et al., 2010; Channan et al., 2014), the Global Tree Canopy Cover (Hansen et al., 2013), the ALOS-PALSAR Forest/Non-Forest Map (Shimada et al., 2014), and the GlobeLand30 (NGCC, 2014; Chen et al., 2015). Table 1 describes these products in detail.

We extracted the coverage of the Philippines from the seven global products then reclassified their original categories, including those of the national product, into two categories: forest and non-forest. Table 1 shows the reclassification procedure. The reclassification generated eight Forest versus Non-Forest maps that we call, respectively, NAMRIA30, CCI300, LANDSAT30, MODIS250, MODIS500, GTCANOPY30, ALOS25, and GLOBELAND30. The number at the end of each name indicates spatial resolution in meters.

To produce the reference data, we generated 10,000 sample points distributed randomly across the spatial extent of the Philippines. We first converted the points into a kml file, which we uploaded to Google Earth. We attempted to classify visually each point as either forest or non-forest based on a > 50% threshold at a 25 m spatial resolution, which is the smallest spatial resolution among the land cover data (Table 1). We classified a point as forest when its corresponding 25 m × 25 m grid contained > 50% tree cover based on visual interpretation and estimation. Otherwise, we classified the point as non-forest.

Some points were easier than others to make a decision concerning forest versus non-forest. Fig. 1 shows an example where the cover of points (b), (d) and (e) is clearer than of points (a) and (c). We classified 9852 of the 10,000 points, because the other 148 points were impossible to identify due to cloud cover, shadow or lack of image. Fig. 2 shows the spatial distribution of these points. Google Earth has a feature that allows the user to select images according to capture date. We were interested in 2010. However, a 2010 image was not available for some points. In such cases, we used the closest available capture date (see Fig. 2). We used these points as reference information for error assessment, thus we call this dataset REFERENCE.

2.2. Comparison and assessment of forest versus non-forest maps

We analyzed the 9852 points where each point is either forest or non-forest in each of the eight Forest versus Non-Forest maps and in the reference data: NAMRIA30, CCI300, LANDSAT30, MODIS250, MODIS500, GTCANOPY30, ALOS25, GLOBELAND30, and REFERENCE. We applied the following procedures.

First, we performed error assessment using the Google Earth data as reference. For each of the eight Forest versus Non-Forest maps, we computed for the forest category the omission disagreement, commission disagreement, and agreement. If a point is forest according to a map and non-forest according to the reference data, then the point is forest commission disagreement for that map. If a point is non-forest

Table 1
Land cover products and their descriptions. The second to the last row shows the reclassification procedure we implemented to produce eight Forest versus Non-Forest maps of the Philippines in 2010.

	Philippine Land Cover (2010)	CCI Land Cover (2010)	Landsat Vegetation Continuous Fields (VCF) (2010)	MODIS Vegetation Continuous Fields (VCF) (2010)	MODIS Land Cover Type product (MCD12Q1) (2010)	ALOS PALSAR-FNF25 (2010)	Global Tree Canopy Cover circa 2010	GlobeLand30 (2010)
Reference	Manuel (2014); DENR (2015)	ESA (2017)	Sexton et al. (2013)	DiMiceli et al. (2011)	Friedl et al. (2010); Channan et al. (2014)	Shimada et al. (2014)	Hansen et al. (2013)	NGCC (2014); Chen et al. (2015)
Primary Satellite Data Source	Landsat, ALOS-AVNIR2, SPOT	MERIS	Landsat	MODIS	MODIS	ALOS-PALSAR	Landsat	Landsat, HJ-1
Spatial Resolution (m)	30 [a]	300	30	250	500	25	30	30
Classification Technique	Object-based classification	Unsupervised classification chain, with machine learning algorithm	Regression tree model	Regression tree model	Decision tree classification algorithm with boosting	Rule-based approach and thresholding	Regression tree model	Pixel-object-knowledge-based method
Number of Classes	14	36	N.A. [b]	N.A. [b]	18	3	N.A. [b]	10
Data for Validation	Field data	GlobCover 2009 validation dataset	Small-footprint lidar measurements in 2005, 2006 and 2008	Field data from two sites in Maryland, and three sites in Brazil	The estimated accuracy was cross-validated using a training site database	Data from Google Earth and the Degree Confluence Project (DCP)	Landsat; MODIS; Google Earth	Google Earth; Landsat; DCP verified points; Online authentic landscape photos
Overall Error	10.6%	26.6% [c]	RMSE = 17.4% [d]	RMSE = 9.5–10.5% [e]	25.2%	10.9% (average)	Forest Loss: 0.4%; Forest Gain: 0.3% [f]	16.5%
Reclassification to Forest and Non-Forest (this study)	Forest: closed forest; open forest; mangrove forest Non-Forest: all other categories	Forest: tree cover, broadleaved, evergreen, closed to open; tree cover, needleleaved, deciduous, closed to open; tree cover, flooded, fresh or brackish water; tree cover, flooded, saline water Non-Forest: all other categories	Forest: pixels with VCF values > 50% − ≤ 100% Non-Forest: pixels with VCF values ≤ 50% and all other categories	Forest: pixels with VCF values > 50% − ≤ 100% Non-Forest: pixels with VCF values ≤ 50% and all other categories	Forest: evergreen needleleaf forest; evergreen broadleaf forest; deciduous needleleaf forest; deciduous broadleaf forest; mixed forest Non-Forest: all other categories	Forest: Forest Non-Forest: non-forest; water	Forest: pixels with VCF values > 50% − ≤100% Non-Forest: pixels with VCF values ≤ 50%	Forest: Forest Non-Forest: all other categories
Name	NAMRIA30	CCI300	LANDSAT30	MODIS250	MODIS500	ALOS25	GTCANOPY30	GLOBELAND30

[a] The land cover data we used was in vector format. It was rasterized to 30 m during reclassification.
[b] Not applicable. These maps have continuous values.
[c] This is the average overall error for the 2015 land cover map (no available specific validation for 2010) using the GlobCover 2009 validation dataset.
[d] Root Mean Square Error between estimated and reference tree cover values.
[e] Root Mean Square Error between percentage of tree cover from MODIS VCF 2010 in each validation site and percentage of tree cover from the ground-based validation data.
[f] Forest loss was defined as a stand-replacement disturbance, whereas forest gain was defined as the inverse of loss, or a non-forest to forest change (2000–2012) (Hansen et al., 2013).

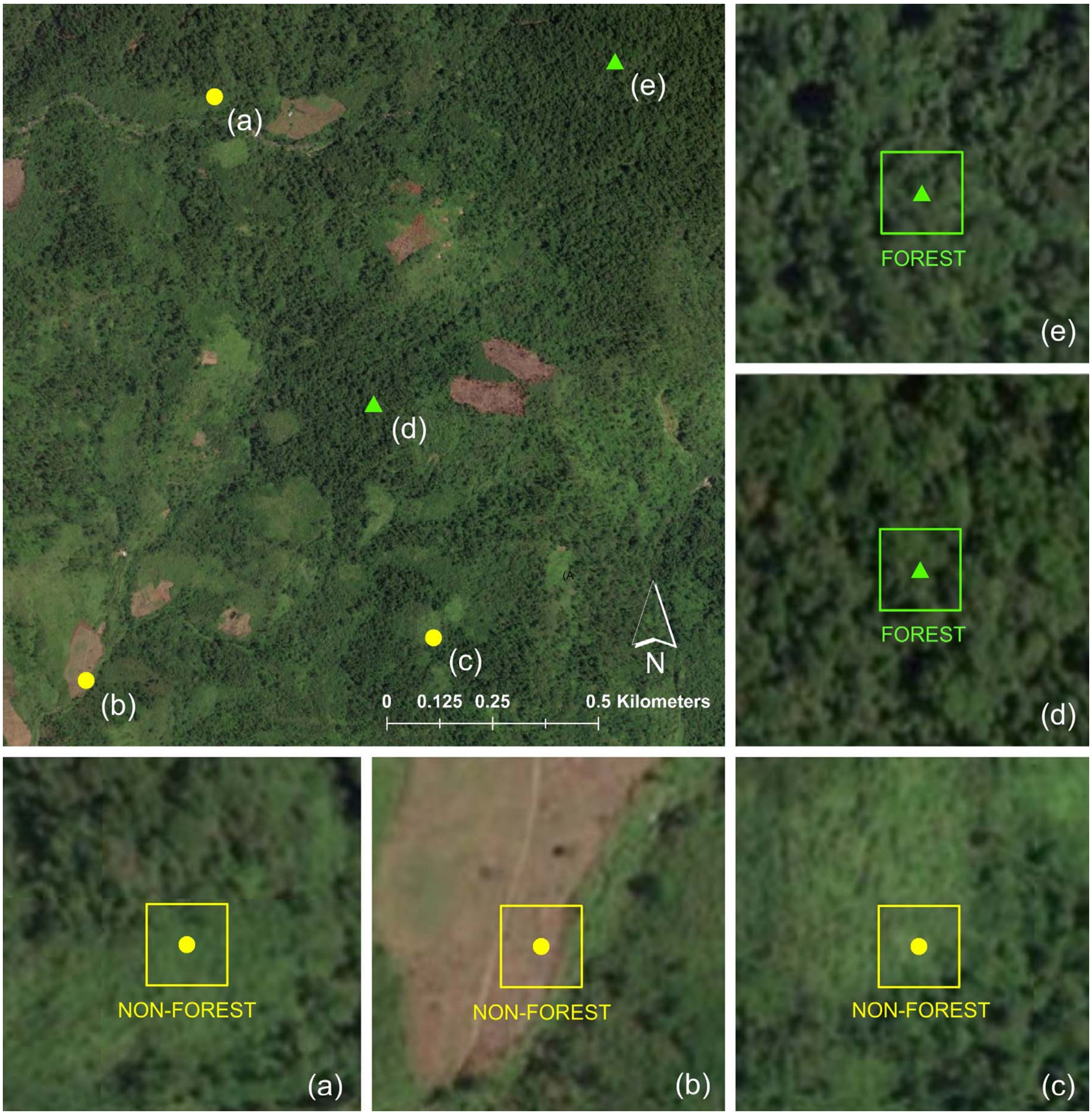

Fig. 1. A Google Earth image with five zoomed-in images that contain sample points displayed as triangles for forest and circles for non-forest. Each of the squares enclosing the sample points measures 25 m × 25 m.

according to a map and forest according to the reference data, then the point is forest omission disagreement. If a point is forest according to a map and forest according to the reference data, then the point is forest agreement.

Second, we separated the disagreement into two parts called quantity and allocation (Pontius and Millones, 2011). Quantity disagreement exists when the area of forest in one map differs from that of the reference data. Allocation disagreement forms when a forest commission point is paired with a forest omission point. We used Eqs. (1)–(3) to compute quantity disagreement (Q), allocation disagreement (A) and total disagreement (T).

$$Q = |Forest\ \ Commision - Forest\ \ Omisison| \tag{1}$$

$$A = 2\ \mathrm{MINIMUM}(Forest\ \ Commission, Forest\ \ Omission) \tag{2}$$

$$T = Q + A \tag{3}$$

Our next two methods examine simultaneously all nine datasets, which consist of the eight Forest versus Non-Forest maps and the reference data. We examined the number of datasets that agree on forest and that agree on non-forest. A point has unanimous agreement when the same category exists in all nine datasets. A point has minimum agreement when five datasets show one category and four datasets show the other category. We computed the percentage of the points under each possibility for the number of datasets that agree on forest or non-forest.

Finally, we created a method to compare the structure of the nine datasets in more detail, as Fig. 3 conveys. The Venn diagrams in Fig. 3 illustrate the concepts of quantity disagreement and allocation disagreement in the context of multiple maps. Each circle represents forest in one of three maps, where outside of the circle represents non-forest. We can envision pair-wise comparisons between any two maps. For example, the disagreement between the two circles at the top of Fig. 3a is the union of the regions called A, AC, B and BC. Fig. 3a shows a situation where all circles are of the same size, meaning all maps show the same quantity of forest, thus quantity disagreement is zero for any pair of maps. In Fig. 3a, the size of omission equals the size of commission for each pair of maps, and all disagreement is due to allocation. Fig. 3b shows a situation where the circles differ in size, thus quantity disagreement exists. Furthermore, the maps in Fig. 3b are not subsets of each other, thus allocation disagreement also exists for each pair of

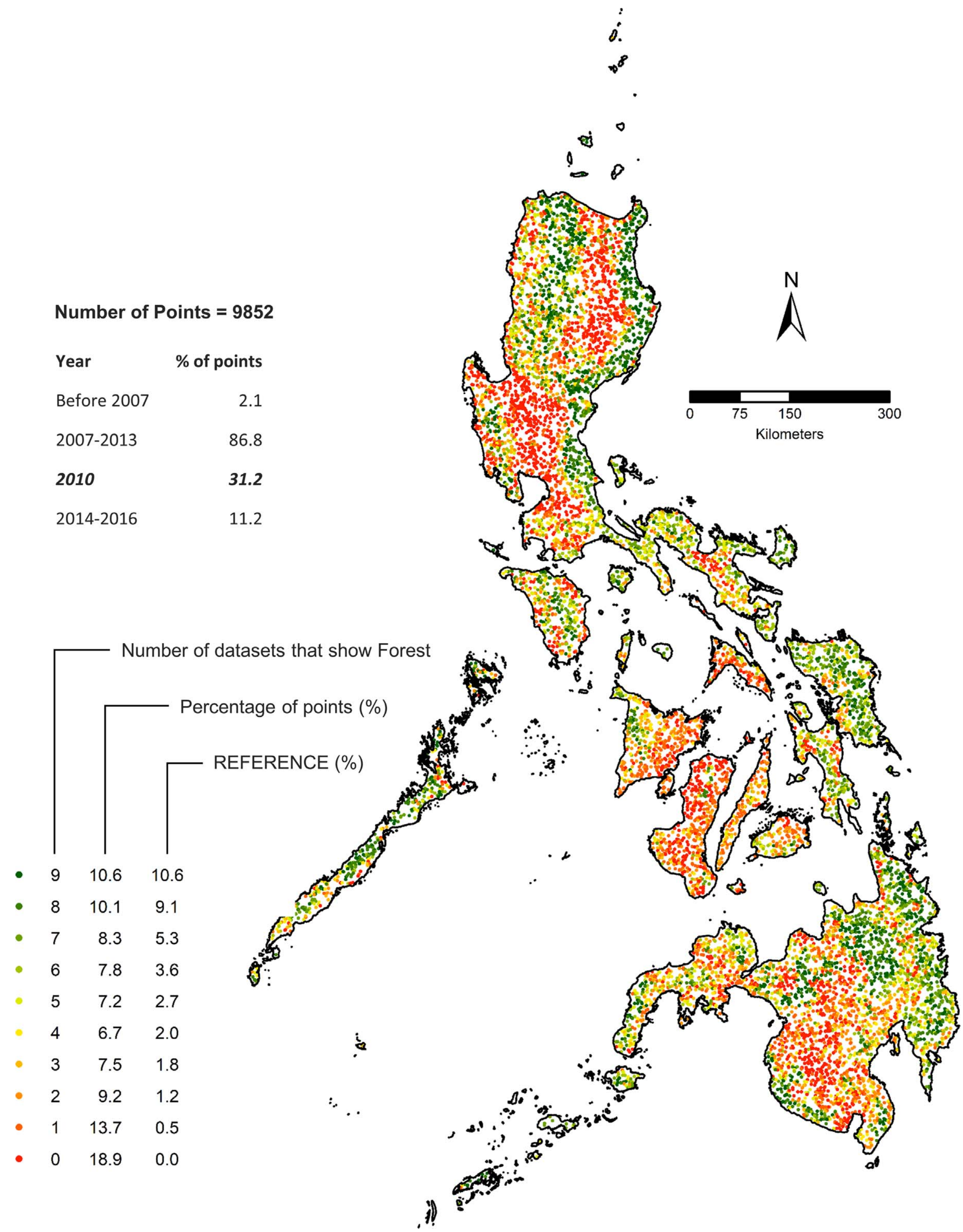

Fig. 2. Spatial distribution of the 9852 sample points. The maximum number of datasets that show Forest is nine, composed of the eight Forest versus Non-Forest maps and the reference data. The REFERENCE column in the lower table shows the number of forest sample points expressed as percentage of points, totalling 36.9%.

maps. Fig. 3c shows a situation where the circles differ in size and are allocated as nested subsets. All disagreement is due to quantity in this situation. Allocation disagreement is zero because either forest commission or forest omission is zero. We used this conceptual diagram to compare all nine datasets simultaneously to quantify the percentage of the points that are allocated in the nested manner of Fig. 3c.

3. Results

Fig. 4 shows the eight Forest versus Non-Forest maps, which have estimates of forest cover ranging from 23% for NAMRIA to 67% for GLOBELAND30. These figures translate to 6.8–19.8 million ha of forest, based on the spatial extent of the maps, which is 29.6 million ha. The REFERENCE estimates 37% forest, implying 10.9 million ha of forest (Fig. 5).

Fig. 5 shows the error assessment using the Google Earth data as

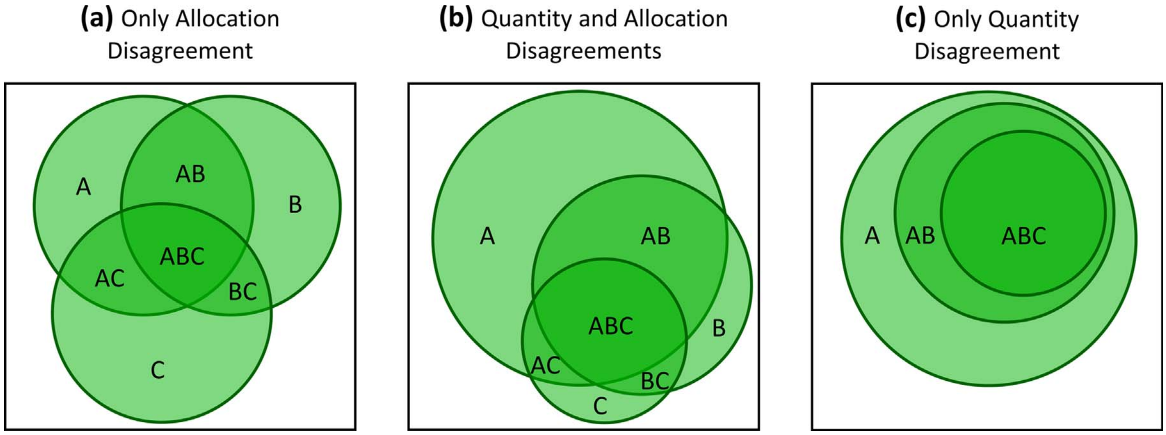

Fig. 3. Venn diagrams to illustrate combinations of quantity disagreement and allocation disagreement for multiple maps.

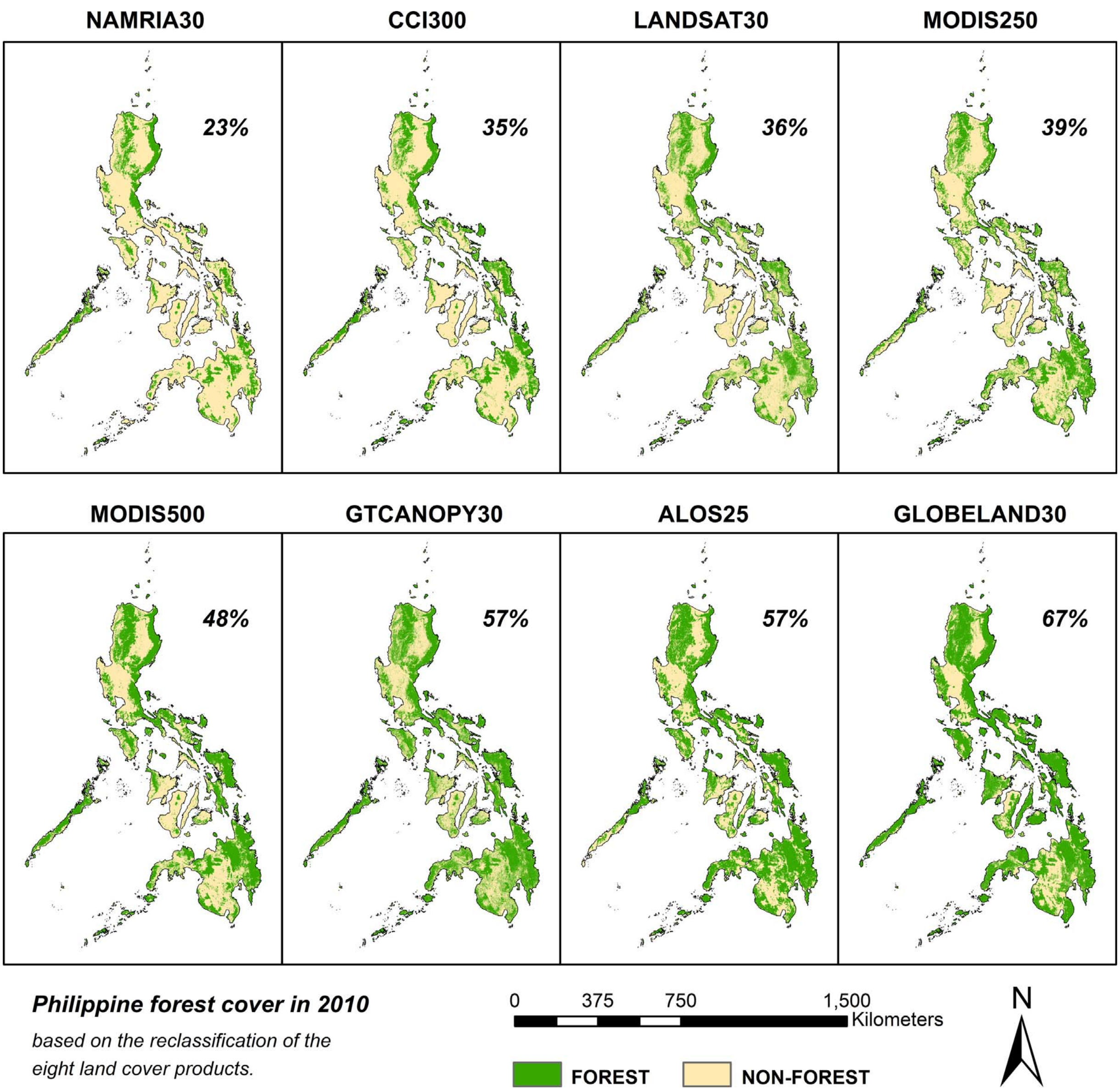

Fig. 4. Forest versus Non-Forest Maps of the Philippines in 2010 according to our reclassification of the eight land cover products. Percentages indicate forest cover relative to the spatial extent of the maps, which is 29.6 million ha.

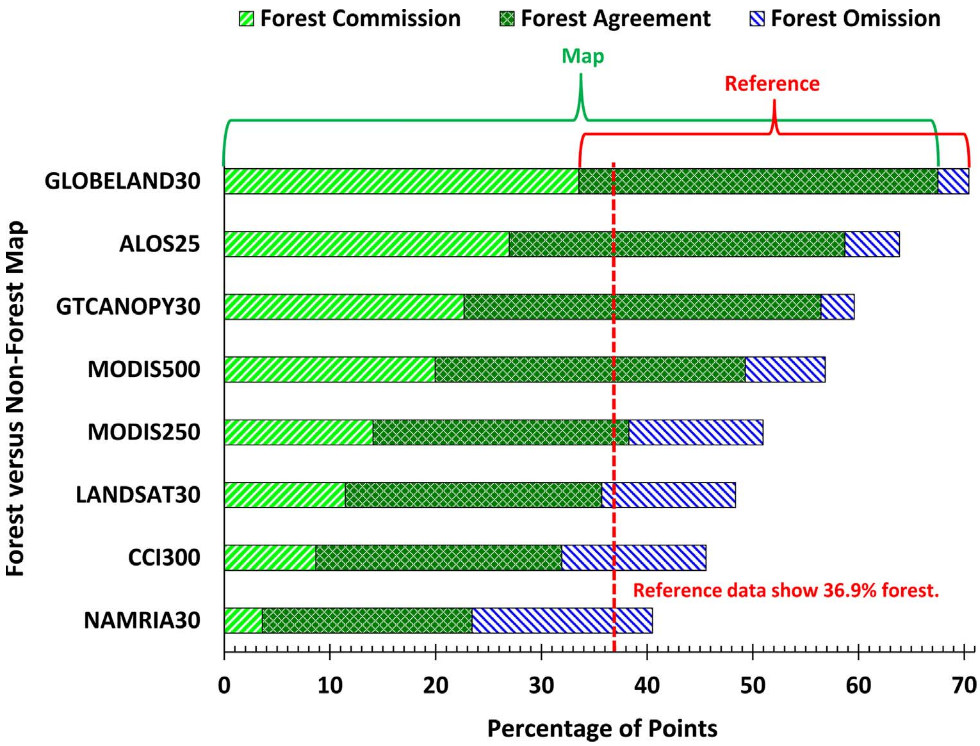

Fig. 5. Error assessment of the eight Forest versus Non-Forest maps.

reference. Each stacked bar forms a Venn diagram. The forest in each map is the union of forest commission and forest agreement. The forest in the reference data is the union of forest agreement and forest omission. Agreement is the intersection of map forest and reference forest. NAMRIA30, CCI300 (10.4 million ha) and LANDSAT30 (10.6 million ha) have less forest than the reference. LANDSAT30 is the map that is closest to the reference in terms of forest quantity.

Fig. 6 presents the two components of disagreement, namely quantity disagreement and allocation disagreement. LANDSAT30 has the smallest quantity agreement with 1.2%, followed by MODIS250 and CCI300 with 1.4% and 5.0%, respectively. On the other hand, GLOBELAND30 had the largest quantity disagreement with 31.8%, followed by ALOS25 and GTCANOPY30 with 21.8% and 19.5%, respectively. Overall, NAMRIA30 had the smallest total disagreement with 20.7%, followed by CCI300 and LANDSAT30 with 22.3% and 24.1%, respectively. By contrast, GLOBELAND30 had the largest total disagreement with 36.5%, followed by ALOS25 and GTCANOPY30 with 32.1% and 25.8%, respectively.

Fig. 7 shows that the nine datasets agree unanimously on 29.5% of the sample points, of which 10.6% are attributable to forest and 18.9% to non-forest. At the opposite extreme, 13.9% of the points show the maximum disagreement, where five datasets agree on the category while the other four datasets show the opposite category.

Fig. 8 indicates the combinations of datasets that agree. The key describes how one letter denotes each dataset. The combination of letters near each slice of the pie indicates the combination of datasets

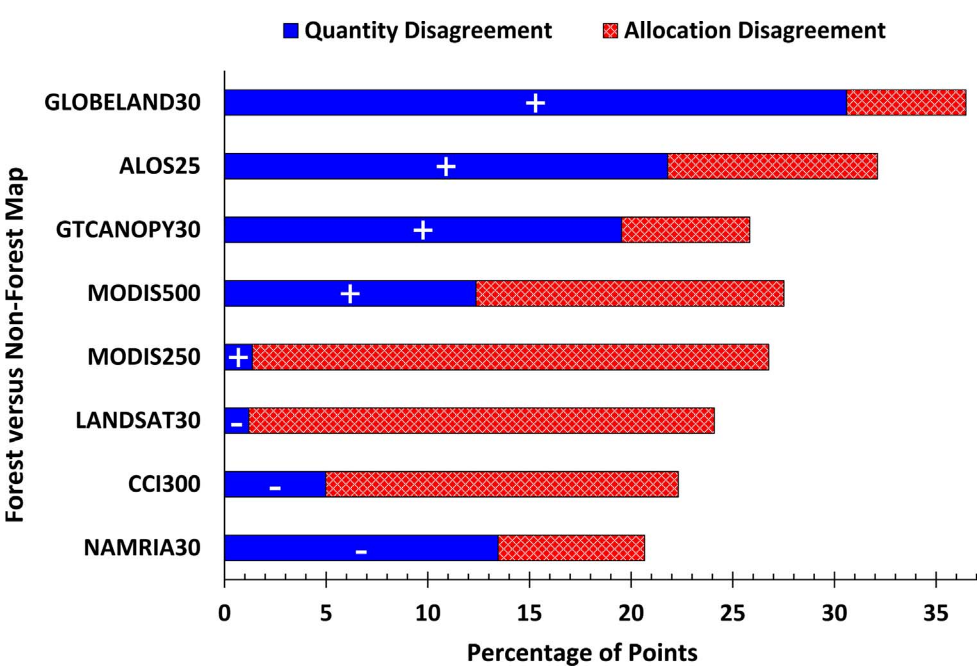

Fig. 6. Quantity and allocation disagreement for each map. The "-" sign indicates the map has less forest than the reference data; the "+" sign indicates the map has more forest than the reference data.

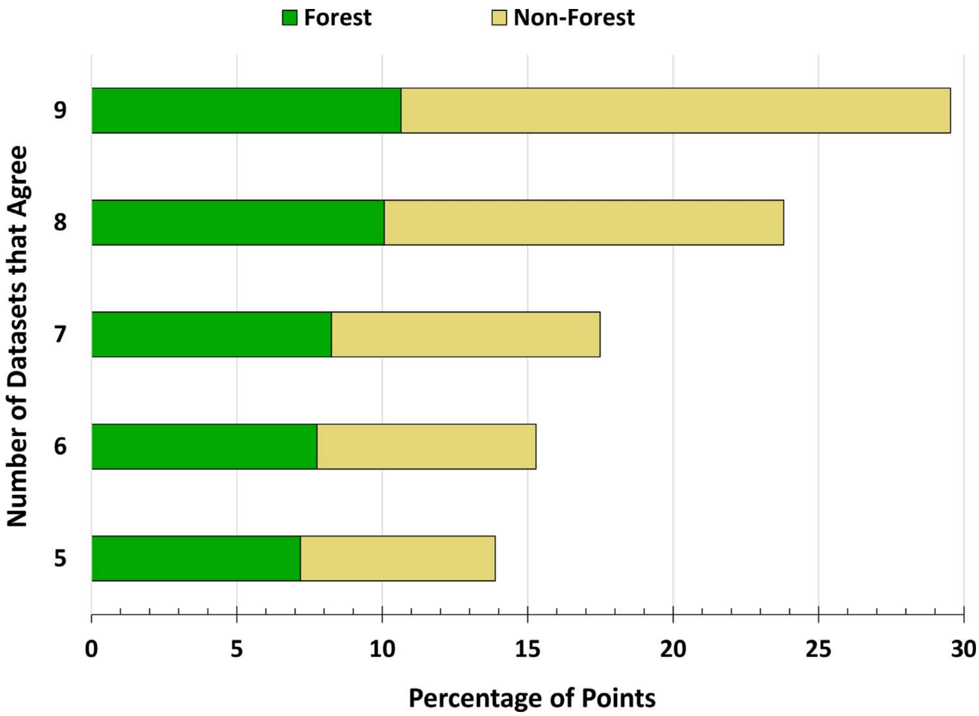

Fig. 7. Number of datasets that agree. The bars sum to 100% of the 9852 sample points.

that agree on forest, where the other datasets simultaneously show non-forest. For example, the slice called GATMDRLCN indicates that all nine datasets unanimously show forest on 10.6% of the sample points. The slice called GATMDRLC indicates that eight datasets show forest while NAMRIA30 (N) shows non-forest on 2.8% of the sample points. The slice called G indicates that GLOBELAND30 shows forest and the other eight datasets show non-forest on 6.8%. The slice called All Non-Forest indicates that all nine datasets show non-forest on 18.9%. Other combinations, called Not Nested, constitute 51.8% of the sample points. Thus 49.2% of the points have a nested structure as in the Venn diagram of Fig. 3c. This nested structure occurs when the forest in a given dataset is a subset of the forest in the datasets that have more forest than the given dataset. This type of nested structure arises when quantity disagreement is the reason for the difference between datasets. Allocation difference between datasets produces the Not-Nested portion of Fig. 8, as in the Venn diagram of Fig. 3b.

4. Discussion

4.1. Disagreements of the eight forest versus non-forest maps with the reference data and their implications

Our results show greater overall errors than the overall errors shown in Table 1. For instance, the land cover product for the GLOBELAND30 map, which contains 10 land cover categories, has 16.5% overall error (NGCC, 2014; Chen et al., 2015; Table 1), but our results show 36.5%

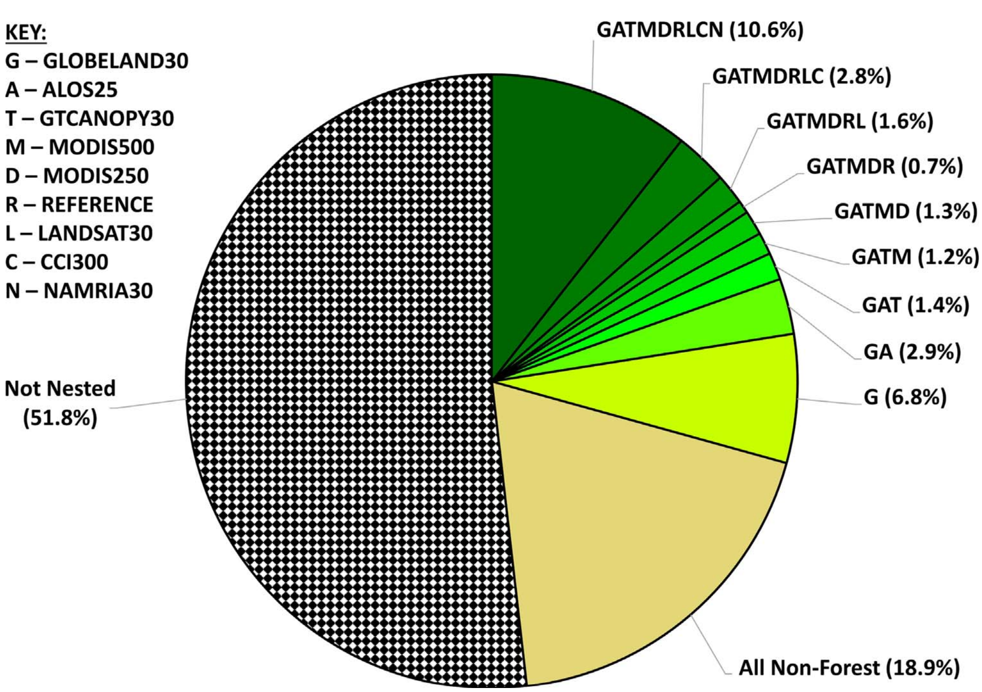

Fig. 8. Percentage of points that show a nested structure on the right and a non-nested structure on the left.

total disagreement with the reference data for the categories forest and non-forest (Figs. 5 and 6). The land cover products for NAMRIA30 and ALOS25 have 10.6% and 10.9% overall error, respectively (Manuel 2014; Shimada et al., 2014; Table 1). However, our results showed much higher total disagreement, 20.7% for NAMRIA30 and 32.1% for ALOS25 (Figs. 5 and 6). The land cover products for MODIS500 and CCI300 have 25.2% and 26.6% overall error, respectively (Friedl et al., 2010; Channan et al., 2014; ESA, 2017; Table 1), which are close to our computed total disagreements of 27.5% and 22.3%.

Our findings are not consistent with some previous findings. For instance, in a similar study in Loess Plateau, China using 2010 land cover products, Yang et al. (2017) found that GLOBELAND30, ALOS25, GTCANOPY30 and LANDSAT30 had overall errors of 3%, 5%, 6% and 7%, respectively. These values are much smaller than our findings for the Philippines, in which our maps had a total disagreement with our reference data of 36.5%, 32.1%, 25.8% and 24.1%, respectively (Fig. 6). Some possible causes of these disparities include differences in Google Earth image interpretation and reclassification procedures for the GTCANOPY30 and LANDSAT30 maps, for which Yang et al. (2017) used > 10% threshold, while we used > 50% threshold. We discuss below the implications of these thresholds. The discrepancies between the results in China and in the Philippines could be due also to the quality of the land cover products, which may not be consistent spatially across regions or countries.

We looked for any systematic association between spatial resolution and the estimated forest size or the disagreement, but found none. The reason might relate to the spatial distribution of forest in the Philippines. If the threshold to define a pixel as forest is that the pixel contains more than half tree cover, then a pixel containing slightly more than half tree cover will be classified as entirely forest, thus that pixel will overestimate forest area. Similarly, a pixel containing slightly less than half tree cover will be classified as entirely non-forest, thus that pixel will underestimate forest area. Our results show that the coarser maps do not have systematic overestimation or underestimation of forest area, which may indicate that the number of pixels that contain slightly less than half tree cover is similar to the number of pixels that contain slightly more than half tree cover.

One must consider whether map errors are important for practical purposes. A potential application of the Forest versus Non-Forest maps of the Philippines is to serve as benchmarks to monitor the impact of the National Greening Program. Reliable benchmarks are also needed to monitor the changes in the value of forest ecosystem services and to assess projects that aim to reduce emissions from deforestation and forest degradation. Therefore, it is important to compare the size of differences between the maps and the reference data to the amount of forest cover change over time. The Philippine forests have shrunk during the last century from 70% to 22% of the country (ESSC, 1999), which is equivalent to about one percentage point every two years. Thus, each percentage point of quantity error in the Forest versus Non-Forest maps can lead to an underestimation or overestimation of two years of net deforestation, assuming the historical deforestation rate. Therefore, our results indicate that the disagreements can have important implications for monitoring of temporal forest cover change.

The reference data estimates that 36.9% of the Philippines is forest (Fig. 5). LANDSAT30 has the quantity of forest with the least difference from the reference data, with a difference of about 1% (Figs. 4 and 5), which is equivalent to about two years of net deforestation considering the historical deforestation rate. However, the threshold we used to reclassify LANDSAT30, GTCANOPY30 and MODIS250 was > 50% (Table 1), which means that only those pixels with VCF values > 50% were classified as forest. If we had used a > 10% threshold, like in the case of Yang et al. (2017), then LANDSAT30's forest estimate could have reached 82%. The forest estimate could have reached 66% and 91% for GTCANOPY30 and MODIS250, respectively. Brinck et al. (2017) used a > 30% threshold in a separate study on high resolution analysis of tropical forest fragmentation and its impact on the global carbon cycle. In fact, previous researchers have used various thresholds, ranging from 10% to 60% (see Sexton et al., 2015). Hansen et al. (2013) used > 50% threshold in their analysis and discussions of global maps of 21st-century forest cover change. Their research gave rise to the land cover product we used to produce GTCANOPY30. GLOBELAND30 had the largest quantity difference compared to the reference data with about 30% (Figs. 4 and 5), which translates to about 60 years of net deforestation. GLOBELAND30's forest estimate of 67% for the Philippines is very close to the 70% forest estimate for the country for the year 1900 (ESSC, 1999).

NAMRIA30 has the least total disagreement with the reference data, but the disagreement is 20.7%. If the purpose is to use the maps as benchmarks for quantity-based national forest cover monitoring from year to year, then quantity disagreement is particularly important. LANDSAT30 has the smallest quantity disagreement with the reference data. This map, however, has 24.1% total disagreement due to its high allocation disagreement. Allocation disagreement is important for subnational forest cover monitoring. Allocation disagreement can also be important in the context of habitat fragmentation monitoring and assessment. Understanding the impacts of forest and habitat fragmentation is important for landscape change and ecosystem services monitoring (Haddad et al., 2015; Mitchell et al., 2014, 2015; Estoque and Murayama, 2016), and forest and biodiversity conservation (Zuidema et al., 1996; Fahrig, 2003; Hill, et al., 2011).

4.2. Potential causes of disagreement

There are more than 800 official definitions relating to the word 'forest' (FAO, 2002; Lund, 2015; Sexton et al., 2015). Sexton et al. (2015) argue that the various definitions of forest account for the disagreement among forest cover estimates. In our study, the variety of definitions of forest is a major source of discrepancy among our eight Forest versus Non-Forest maps, similar to other studies that compare remote sensing-derived forest and land cover products (Cabral et al., 2010; Bai et al., 2014; Congalton et al., 2014; Churches et al., 2014; Tsendbazar et al., 2015; Yang et al., 2017).

GLOBELAND30 defined forest as "lands covered with trees, with vegetation cover over 30%, including deciduous and coniferous forests, and sparse woodland with cover 10–30%, etc." (NGCC 2014, p. 6). ALOS25 used region-specific thresholds for L-band backscatter values to extract forest cover (Shimada et al., 2014). In contrast, MODIS500, CCI300 and NAMRIA30 used various sub-categories of forest (Friedl et al., 2010; Manuel, 2014; ESA, 2017). MODIS250 and LANDSAT30 present forest cover data in terms of a vegetation fraction, called vegetation continuous fields (VCF). GTCANOPY uses fraction of tree canopy cover.

An entire segment or pixel is classified as entirely forest when it meets a pre-defined threshold. As discussed above, thresholds can vary (Sexton et al., 2015). For the Philippines, the > 50% threshold we applied to MODIS250 and LANDSAT30 resulted in a forest estimate that is close to the reference data (Figs. 4 and 5). However, the > 30% threshold NGCC (2014) applied to GLOBELAND30 and the > 50% threshold we applied to GTCANOPY30 and MODIS500 resulted in the overestimation of forest cover (Figs. 4 and 5). This indicates that a higher or more conservative threshold for these maps is needed for the case of the Philippines.

An extensive calibration procedure is required for forest classification techniques that employ thresholds based on remote sensing image properties such as spectral properties as used in MODIS500 (Friedl et al., 2010) and L-band backscatter values as used in ALOS25 (Shimada et al., 2014). However, like in the case of vegetation fraction, various thresholds of spectral properties and L-band backscatter values can also produce various estimates of forest quantities. Nevertheless, one advantage of threshold-based classification techniques is that the discrepancies between the estimates can be traced back to the threshold values, especially when most of the disagreement is due to quantity.

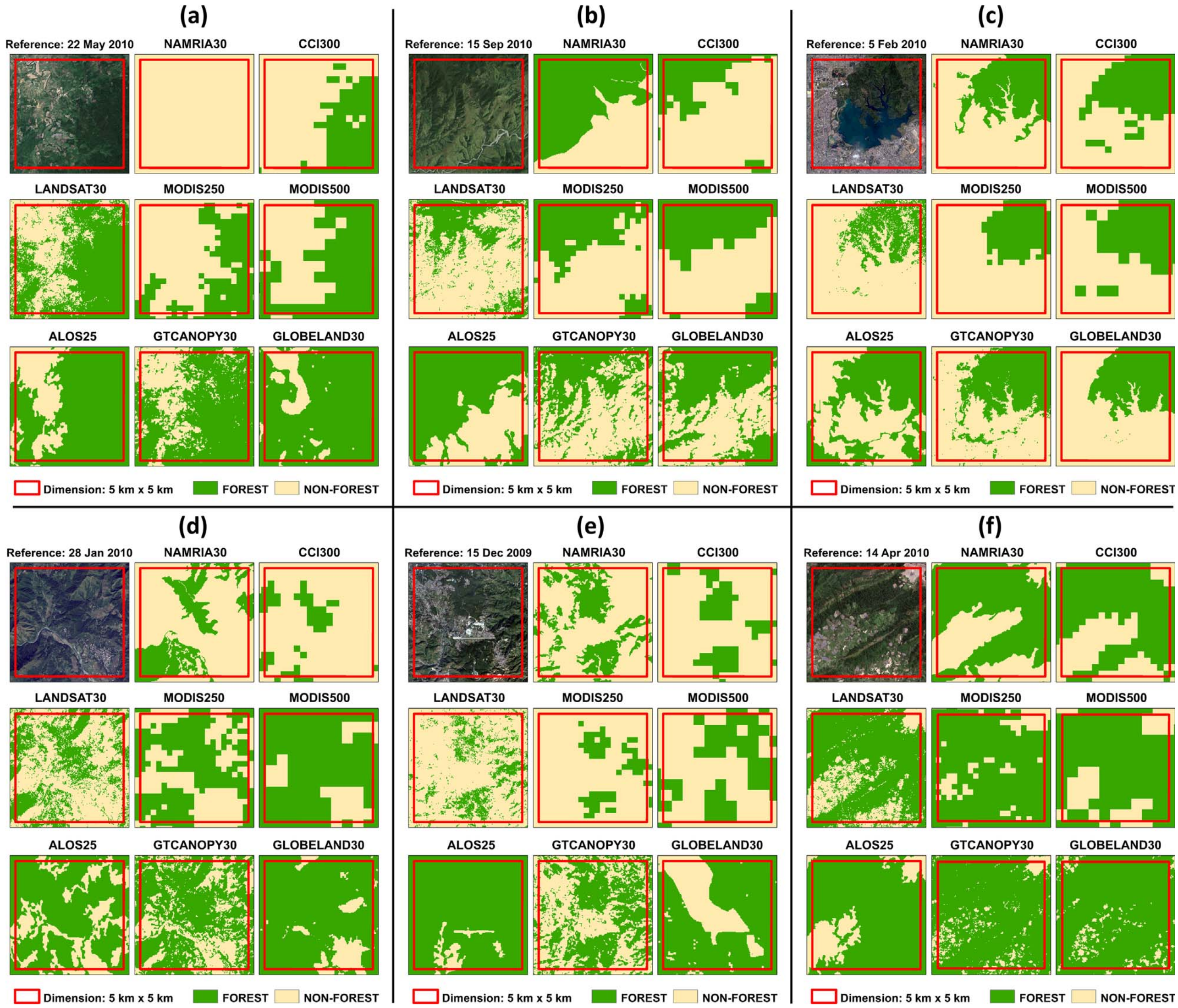

Fig. 9. Six 5 km × 5 km Google Earth reference images and the corresponding eight Forest versus Non-Forest maps, showing: (a) quantity disagreement due to forest omission for NAMRIA30, (b) allocation disagreement, (c) clear reference image, (d) ambiguous reference image, (e) clear forest commission for ALOS25 and GLOBELAND30, and (f) forest commission for MODIS250, GTCANOPY30 and GLOBELAND30.

On the other hand, a classification procedure that considers various forest types gives more information than a classification procedure that considers only two general categories such as forest and non-forest. If maps' legends contain identical forest types, then map comparison is straightforward. However, a classification procedure based on mixed categories poses problems to end-users because mixed categories often lack clear definitions (Bai et al., 2014; Congalton et al., 2014). It is also not clear whether remote sensing imagery can distinguish properly among mixed categories, as well as categories such as closed forest and open forest.

In addition to forest definition, thresholding procedure and classification scheme, classification errors can also be due to clouds, haze, shadows, landscape characteristics, and method-related factors such as quality of training samples and algorithms. Users of Landsat imagery encounter these issues frequently (Bodart et al., 2013; Sexton et al., 2013; Chen et al., 2015). Fig. 9 shows some landscape segments where the eight Forest versus Non-Forest maps have omitted and/or committed forest due to the above-mentioned factors or their combinations.

Seasonal variation can also affect forest estimates. Remote sensing images captured in different seasons can produce substantially different classification results of the same geographic region (Bodart et al., 2013). Multi-date images might have been used to produce all the eight land cover products we used in this study. However, the land cover products lack readily available metadata that would allow us to understand the effect of seasonality.

ALOS-PALSAR data are becoming increasingly popular for forest mapping. One reason is that ALOS-PALSAR data are cloud-free. Forest areas exhibit higher L-band backscatter than non-forest areas, facilitating the mapping of forest and detection of deforested areas (JAXA-EORC, 2010; Shimada et al., 2011, 2014; Dong et al., 2014; Thapa et al., 2014; Qin et al., 2016). Region-specific thresholds for L-band backscatter values were used for the data we analyzed (Shimada et al., 2014), but our results suggest that there is still a need to refine the thresholds for Philippine forests. For example, Figs. 9c and e show confusion of forest with urban in ALOS25, which we suspect is due to error in thresholding. Thapa et al. (2014) argued that human settlements such as urban areas need careful attention when using PALSAR imagery and threshold-based classification procedures.

4.3. Advantages and challenges of reference data collection from Google Earth

Google Earth is becoming increasingly popular as a source of reference information (Friedl et al., 2010; Estoque et al., 2012, 2015; Shimada et al., 2014; Chen et al., 2015; Estoque and Murayama, 2015; ESA, 2017; Yang et al., 2017). Google Earth allows for virtual fieldwork, thus substantially reduces the need for costly ground field surveys. Google Earth has coverage for areas that are impossible to reach during field surveys. Also, virtual fieldwork can go back in time.

However, Google Earth also has some limitations in some regions due to incomplete coverage, unclear images, or dense clouds, which are especially prominent in wet tropical regions like the Philippines. Poor image quality introduces ambiguity and hence subjectivity in visual interpretation. Landscape characteristics can make it challenging to classify each point as forest or non-forest even where the Google Earth images are clear. It can also be difficult and subjective to decide what qualifies as a forest where trees are sparsely scattered. Fig. 9 illustrates a range of clarity in the reference data. The Google Earth image in Fig. 9c distinguishes clearly between forest and non-forest. However, forest is ambiguous for much of the Google Earth image in Fig. 9d, which has mountain shadows and a low density of trees. The Forest versus Non-Forest maps agree with each other in Fig. 9c more than in Fig. 9d.

5. Conclusions

We compared and assessed eight remotely sensed maps of Philippine forest cover in the year 2010: NAMRIA30, CCI300, LANDSAT30, MODIS250, MODIS500, GTCANOPY30, ALOS25, and GLOBELAND30. The proportion of the Philippines covered with forest ranges among the eight maps from 23% for NAMRIA30 to 67% for GLOBELAND30. This range is similar to the estimated change in forest percentage during the previous century – the Philippines was 70% forest in 1900 and 22% in 1998. The Google Earth reference data estimates forest cover at 37%. NAMRIA30 had the lowest overall disagreement with the reference data, while GLOBELAND30 had the highest. LANDSAT30 had the lowest quantity disagreement, while GLOBELAND30 also had the highest. Approximately half of the sample points showed the forest category in a nested structure, where the forest in a given dataset is a subset of the forest in datasets that show more forest than the given dataset. This simultaneous comparison indicates that the variation in the quantity of forest is a substantial reason for the overall variation among the datasets. We suspect that the variation among the datasets relates to the combined effects of the various definitions of forest and classification errors. Scientists should consider these observations when producing future maps and when establishing benchmarks for forest cover monitoring. Policy makers should be aware of the current limitations of forest cover data in the Philippines.

Acknowledgements

The first author was supported by the Japan Society for the Promotion of Science through Grant-in-Aid for Research Activity Start-Up: No. 15H06067, 2015-16 (Representative: Ronald C. Estoque) and Grant-in-Aid for Challenging Exploratory Research No. 16K12816, 2016-2018 (Representative: Yuji Murayama). Any opinions, findings, conclusions, or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of their respective organizations, as well as the funders. The authors also acknowledge the: (1) Land Resource Division of NAMRIA's Resource Data Analysis Branch for providing the 2010 Philippine Land Cover data, (2) producers of the global land cover products that were used, and (3) anonymous reviewers for their constructive suggestions.

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